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Temperature shocks, short-term growth and poverty thresholds: Evidence from rural Tanzania

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ABSTRACT

Using the LSMS-ISA Tanzania National Panel Survey by the World Bank, we study the relationship between rural household consumption growth and temperature shocks over the period 2008–2013. Temperature shocks have a negative and significant impact on household growth if their initial consumption lies below a critical threshold. As such, temperature shocks slow income convergence among households, at least in the short run. Crop yields and total factor productivity in agriculture are the main transmission channels. Extrapolating from short-term elasticities to long-run phenomena, these findings support the Schelling Conjecture: economic development would help poor farming households to reduce the impacts of climate change. Hence, closing the yield gap, modernizing agriculture and favouring the structural transformation of the economy are all crucial issues for adaptation of farmers to the negative effects of global warming.

1. Introduction

Poorer countries are generally found to be more vulnerable to climate change and weather variability. Many would suspect that poorer people are more vulnerable too, but research is scarce. As Tol (2016) notes, if the pattern of vulnerability observed between countries also holds within countries, this would strengthen concerns about climate change, but there is lack of quantification of the intra-country distributional implications of the impacts of climate change.

We shed light on the following questions: does weather and, by implication climate, affect the pattern of economic growth of farm households in a developing country? Is a weather- or climate-induced poverty trap plausible? To this end, we use the empirical tools and models of development economics to examine the link between short-term household welfare dynamics and temperature shocks in rural Tanzania. Specifically, we employ a micro-growth model (borrowed from the macro-growth literature) and test for convergence among households and for the significance of weather shocks as determinants of growth, while controlling for heterogeneity. Then, we test for the presence of consumption thresholds with respect to the impacts of temperature shocks. Finally, guided by previous theoretical and empirical literature, we test potential transmission channels, viz. agricultural productivity, crop yields and asset growth, that may explain heterogeneity of impacts and the lack of consumption smoothing.

This paper thus speaks to two distinct strands of research: the development literature on poverty traps, that investigates the issues of poverty persistence, growth divergence and multiple equilibria; and the emerging climate-economy literature that studies weather elasticities of growth. Our identification strategy looks at short-run weather variations to infer changes over longer periods, exploiting the tight linkages between short-run weather shocks and climate change (Dell, Jones, & Olken, 2014).

Tanzania is an appropriate setting for such a study for several reasons. It is commonly accepted that the future impacts of climate change will disproportionately affect poorer and hotter countries (Tol, 2018), and especially people living in rural, remote and scarcely populated areas, whose main source of income is agriculture. Sub-Saharan Africa, in particular, has been identified as one of the

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most vulnerable parts of the world to climate change (Field et al., 2014). Tanzania is a poor and hot Sub-Saharan country, where in 2015 68% of the population lived in rural areas.[1] It is typically classified as a country under high risk from the impacts of future climate change: temperatures in the country are predicted to rise 2–4 °C by 2100, with warming more concentrated during the dry season and in the interior parts of the country (Rowhani, Lobell, Linderman, & Ramankutty, 2011). Ahmed et al. (2011) underline the importance of agriculture, which accounts for half of GDP and employs 80 percent of the labour force. Agriculture in the country is primarily rain-fed, with only two percent of arable land having irrigation facilities. Tanzania is also a country which exhibits quite large climatic diversity, varying from tropical at the coast to temperate in the highlands (Rowhani et al., 2011). Finally, there are good data: we use the Living Standard Measurement Survey (LSMS) – Integrated Survey on Agriculture (ISA) Tanzania National Panel Survey by the World Bank, a three-wave household longitudinal dataset covering the period 2008–2013.

The results show striking heterogeneity: temperature-induced consumption shocks only affect the poorest households. Rural households suffer from a negative and significant contemporaneous slowdown of growth due to temperature shocks, but only if their initial consumption level lies below a critical threshold. In other words, hot weather slows convergence among households, and enhances inequalities. The main transmission channels are agricultural yields and agricultural total factor productivity (TFP). No impact on asset growth is found, suggesting that asset smoothing is taking place. That is, poor households choose to destabilize their consumption in order not to have to sell their assets, or do not have enough assets to sell to cope with the fall in income caused by temperature shocks. We find a *poverty-induced climate trap* rather than a *climate-induced poverty trap*, since the negative impacts of temperature shocks are significant only for households whose initial consumption level lies below a critical threshold. It follows that a clear-cut policy implication for policymakers in Tanzania is to prioritize modernizing agriculture. The reward is twofold: closing the yield gap and making farmers less *vulnerable* to climate change (Tol, 2016).

Given the short-run nature of this dataset, our capacity to assess convergence is limited, and we can only cautiously infer long-run trends. Also, we do not directly test for the presence of multiple equilibria and hence for the existence of a poverty trap. Under a classic 'poverty trap' threshold, households are trapped in an equilibrium with permanently low income, whereas here we only check whether there is a consumption threshold above which temperature impacts turn insignificant, i.e. whether impacts disappear as households grow richer. Deceleration is not bifurcation, as noted by Dercon (2004) and Jalan and Ravallion (2002): temperature shocks slow the convergence process but they do not reverse it, at least not in the time frame of our data. Finally, interpreting our weather results with respect to climate change is hard, given the intrinsic difference between short-run weather shocks and long-run changes in climate.

The contributions of this paper are the following. First, it complements aggregate growth – climate empirics with available micro panel data, providing evidence on the (short-run) micro causal relationship between weather anomalies, poverty and growth. Second, it links the weather-economic growth literature with the development literature on poverty traps, by applying the tools and models of the latter to the research questions of the former. Third, it contributes to the development literature, by testing for consumption *vs* asset smoothing, which has rarely been done according to Carter and Lybbert (2012), and by showing that, when controlling for temperature shocks (often ignored in development literature), precipitation impacts are insignificant and close to zero.

The rest of this paper is arranged as follows. Section 2 reviews the relevant literature. Section 3 illustrates the empirical framework and the identification strategy. Section 4 describes data and provides introductory descriptive statistics. Section 5 presents the results of the empirical analysis. Section 6 conducts a host of robustness checks. Section 7 investigates the channels of the heterogeneity of impacts. Section 8 wraps up, illustrates the policy implications of the analysis with regard to climate change, adds *caveats* and concludes.

2. Literature review

A growing body of empirical work focusing on the weather/climate-economy relationship has recently emerged with the aim to understand and quantify the future impacts of climate change on human welfare. In a thorough review of this literature Dell et al. (2014) notice how earlier cross-sectional works (Dell, Jones, & Olken, 2009; Gallup, Sachs, & Mellinger, 1999; Nordhaus, 2006), whose validity is challenged by endogeneity and omitted variable bias, have recently been replaced by more appropriate and robust panel methods, both macro (Bansal & Ochoa, 2011; Burke, Hsiang, & Miguel, 2015; Dell, Jones, & Olken, 2012; Hsiang & Jina, 2014; Hsiang, 2010) and micro (Cachon, Gallino, & Olivares, 2012; Dercon and Christiaensen, 2011; Graff Zivin & Neidell, 2014; Heal & Park, 2015; Niemelä, Hannula, Rautio, Reijula, & Railio, 2002; Schlenker & Lobell, 2010; Sudarshan & Tewari, 2013). This literature typically uses weather shocks, which are hard to extrapolate to climate change, although some studies uses changes over longer periods to look at climate variation or interactions between climate and weather variables.

The main finding of this emerging literature is that weather affects economic activity and growth through a wide range of channels, particularly in poor countries.[2] Agriculture, health and labour productivity have been frequently cited as the most important transmission channels of such impacts. Several studies have investigated the relationship between crop yields and weather variability, starting from the plausible assumption that extreme temperatures and too much and too little rainfall may damage crops (Challinor, Wheeler, Craufurd, & Slingo, 2005; Li et al., 2010; Porter & Semenov, 2005; Rowhani et al., 2011; Schlenker & Lobell, 2010; Welch et al., 2010). Low crop yields could be one of the reasons why smallholder farmers are trapped in poverty (Barrett & Swallow, 2006; Sachs, 2008; Tittonell & Giller, 2013). Barreca (2012), Burgess, Deschenes, Donaldson, and Greenstone (2011), Deschênes and Greenstone (2011) and Goldberg, Gasparrini, Armstrong, and Valois (2011) have documented the effects of temperature and heat waves on health, particularly mortality, using panel methods. (Cachon, Gallino, et al., 2012; Cachon et al., 2012; Graff Zivin & Neidell, 2014; Heal & Park, 2015; Niemelä et al., 2002; Park, 2017; Sudarshan & Tewari, 2013) have found effects of temperature on the productivity of workers, especially on those who work outdoors.

In parallel, the development literature looks at the impacts of weather shocks on household welfare, vulnerability and poverty. This literature uses weather variation as an instrument to study non-climatic relationships. Paxson (1992) found that unexpected rainfall shocks do not have serious welfare consequences for Thai

[1] http://data.worldbank.org/indicator/SP.RUR.TOTL.ZS?locations=TZ.

[2] These panel estimates have then been employed and calibrated *ad hoc* in simulation studies on the impacts of future climate change (Lemoine & Kapnick, 2015; Moore & Diaz, 2015) to provide empirically-grounded impact estimates for Integrated Assessment Models (IAMs), so to overcome the critiques about the arbitrary choice of crucial parameters like the damage function and climate sensitivity (Pindyck, 2012, 2013; Stern, 2013; Weitzman, 2009, 2010).

farmer households, because they used savings and dissavings to buffer consumption from income shocks. Other papers showed that the insurance strategies adopted by poor farmers against shocks are only partial so that a reduction in crop yields would negatively impact consumption (Fafchamps, Udry, & Czukas, 1998; Morduch, 1995; Townsend, 1995). Households might not be able to smooth their consumption in response to income fluctuations due to credit or liquidity constraints (Hirvonen, 2016; Morduch, 1995; Rosenzweig & Wolpin, 1993). Uninsured risk may cause poverty due to two distinct mechanisms (Dercon, 2004). Since poorer farmers are generally risk-averse, risk *ex-ante* changes behaviour such as precautionary saving and avoiding profitable but risky opportunities (Dercon, 1996, 2004; Elbers, Gunning, & Kinsey, 2007). *Ex post*, temporary shocks can affect long-term outcomes (Carter, Little, Mogues, & Negatu, 2007; Dercon & Christiaensen, 2011; Dercon & Krishnan, 2000; Dercon, 2004; Dercon, Hoddinott, & Woldehanna, 2005; Reis, 2009). This permanent effect of temporary shocks has been typically explained by asset smoothing (Barrett & Carter, 2013; Carter & Barrett, 2006; Carter et al., 2007). Other studies have focused on the possibility of long-run impacts of weather shocks on household welfare (Alderman, Hoddinott & Kinsey, 2006; Hoddinott & Kinsey, 2001)

In the macro growth literature, two alternatives to the neoclassical growth model and the implied income convergence have emerged: club convergence (Baumol, 1986; De Long, 1988; Quah, 1996, 1997) and thresholds and multiple equilibria (Azariadis & Drazen, 1990; Hansen, 1999; Murphy, Shleifer, & Vishny, 1989). At the micro level, as Carter and Barrett (2006) argue, individuals have intrinsic characteristics that determine their ultimate equilibrium level of well-being, and there are mechanisms that generate multiple equilibria. Testing this empirically is hard, as noticed by Barrett and Carter (2013), Carter and Barrett (2006) and Jalan and Ravallion (2002), due to the lack of sufficiently long panels at the household level in developing countries.

Several studies provide evidence of significant persistence in poverty. Some focus on income and consumption growth (Dercon, 2004; Jalan & Ravallion, 2002). Dercon (2004) discovers persistence of shocks, acknowledging that this does not imply permanent effects. Jalan and Ravallion (2002) find evidence for "geographic poverty traps", i.e. a scenario in which the welfare of a household living in a well-endowed area grows while the welfare of an otherwise identical household in an unfavourable geographic area stagnates. Other studies use asset growth as the dependent variable to disentangle structural poverty from transitory poverty. Carter et al. (2007) show that asset-based poverty traps are consistent with the post-shock growth experiences in Honduras after Hurricane Mitch and in Ethiopia after the drought of the late 1990s. They also provide empirical support for "asset smoothing": households with few assets voluntarily destabilize consumption so not to sell assets. Carter and Lybbert (2012) apply threshold estimation techniques to panel data for West Africa, finding support for asset, and not consumption, smoothing in response to external shocks. Barrett et al. (2006) examine welfare dynamics in rural Kenya and Madagascar and find that poor households defend their critical asset levels through asset smoothing, even if this comes at the cost of an immediate reduction in consumption.

3. Empirical framework and identification strategy

Our empirical framework belongs to the strand of the literature that looks at growth in developing countries by using micro-level data, drawing in particular on the works of Carter et al. (2007), Dercon (2004), Jalan and Ravallion (2002). We assess convergence by using a standard empirical growth model, in a framework borrowed from the macro literature (Mankiw, Romer, & Weil, 1992), where growth rates are assumed to be negatively related to the initial income levels:

$$lnY_{it} - lnY_{it-1} = \alpha lnY_{it-1} + \beta \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} + \mu_i + q_{it} + w_t + \theta_{rt} + \varepsilon_{it} \quad (1)$$

In this equation, the left-hand side variable is the annualised growth rate in annual household per adult-equivalent[3] consumption between t and $t-1$, and lnY_{it-1} is household per adult-equivalent lagged consumption.[4] The coefficient α, if negative and statistically significant, would indicate, on average, convergence among households.

In all our specifications, Y_{it} either denotes food consumption or total consumption.

We use two different dependent variables because looking only at food consumption growth one may confound the impact of weather shocks with the effects of relative price changes. In fact, due to changes in the ratio between food *vs* non-food prices, food consumption may follow a different growth path from total consumption. While Dercon (2004), due to lack of data availability for non-food expenditure, had to largely limit his analysis to food consumption growth, we employ both to address this concern. The inclusion of lagged consumption level as an independent regressor may raise concerns about endogeneity. However, endogeneity tests, based on the difference of two Sargan-Hansen statistics – one for the equation with the smaller set of instruments, where lagged consumption is treated as endogenous and instrumented with asset and education levels at $t-1$, and one for the equation with the larger set of instruments, where lagged consumption is treated as exogenous – do not reject the assumption of exogeneity of this variable (see Table A.1). Furthermore, the core findings do not change when we use other estimation methods (see Section 6) which treat lagged consumption level as endogenous.

This basic empirical growth model is augmented to investigate the potential impacts of weather shocks. $\Delta Temp_{gt}$andΔPre_{gt} are temperature and precipitation shocks, where 'shocks' mean 'anomalies' in the sense defined by Dell et al. (2014), i.e. our weather variables are calculated as the difference between their average values in the period between interviews and the long-run means, divided by the long-run standard deviation.[5] This means we assume that level changes matter not only in an absolute sense but also, more importantly, in terms of deviation from their long-run averages. Given we have a short-run panel and only limited climatic variation, this choice of the weather functional form suits better the nature of our data.

A common practice in the development literature on growth and shocks is to only include rainfall in the empirical analysis, ignoring the potential role of temperature as a determinant of

[3] We use an adult-equivalent scale that was already included in the dataset instead of a per capita measure, since per capita measures would underestimate the welfare of households with children with respect to families with no children, and the welfare of large households with respect to small households, as stressed in the Basic Information Document of the original LSMS-ISA surveys. Basic Information Documents for the surveys are available at the following link: http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,contentMDK:23635561~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html.

[4] In the spirit of Jalan and Ravallion (2002) and Dercon (2004) we assumed that the lagged consumption term in our empirical equation does not reflect only reversion to the mean consumption of the household, but also assesses the presence of conditional convergence in household data. This is a reasonable assumption which is actually in line with the findings from previous literature. Since we use household fixed-effects in our empirical estimation, we could not include initial consumption levels because they are time-invariant. Hence the choice of including lagged levels, which in a panel with only three waves is in practice very similar.

[5] The subscript g indicates temperature and precipitation variables are observed at the grid level.

household growth. Indeed, climate literature (Auffhammer, Hsiang, Schlenker, & Sobel, 2013; Dell et al., 2014) has warned against the risk of omitted variable bias when dealing with the effects of weather regressors, and recommends to always include at least both temperature and precipitation as independent variables. Since the two are closely correlated, excluding temperature, as commonly done in many empirical development works, may mean attributing to precipitation shocks an impact which could be due to temperature. We avoid this risk by including both.

To capture potential heterogeneity of impacts, we also interact weather shocks with dummies for being "poor" and for living in "hot" areas, as well as with dummies for initial consumption quartiles, following Carter et al. (2007).[6]

Other than weather shocks, we include two sets of control variables. Z_{it} is a vegetation time series which includes variables providing data on the start of the wettest quarter, average changes in greenness, and onsets of greenness increase and decrease. These vegetation variables were already included in the original World Bank data as part of the Integrated Survey on Agriculture (ISA); we chose to add them in the regression following the advice in Auffhammer et al. (2013) and Dell et al. (2014): it is important to include a rich set of climatic variables in the regression (when available), given the risk of omitted variable bias due to the fact climatic variables are always highly correlated.[7]

X_{it} are household controls, which include household size, the square of household size, the age of the household head and its squared term, a dummy for the gender of the household head, average years of education among adults, the number of infants (i.e. <5-year old) and dummies capturing a variety of self-reported shocks, both idiosyncratic (illness and deaths of household members) and covariate (e.g. market) shocks. The inclusion of control variables reduces the risk of omitted variable bias and provides smaller standard errors in the estimates.

As for the other elements in the equation, $\mu_i$are household fixed effects;q_{it} are quarter of year dummies to capture when the interview took place; w_t are wave dummies; θ_{rt} are region-year fixed effects, to allow for differentiated time trends in different regions and capture idiosyncratic local shocks, as suggested by Dell et al. (2012); ε_{it} are error terms clustered simultaneously at the Enumeration Areas (EAs) and wave levels, following the two-way clustering recommended by Cameron, Gelbach, and Miller (2011). EAs are the main stratification level in the NPS surveys and also the closest unit to the grid level where temperature and precipitation are observed; furthermore, in most rural areas, EAs are defined by village boundaries.[8]

After finding heterogeneity, we try to detect a critical consumption threshold for the significance of temperature impacts. In order to do so, we employed the Hansen (1999) threshold estimator following the approach by Carter et al. (2007). This model distinguishes two impact regimes conditional to a critical value of lagged (pre-shock) consumption level:

$$lnY_{it} - lnY_{it-1} = \begin{cases} \alpha lnY_{it-1} + \beta^l \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} \\ +\mu_i + q_{it} + w_t + \theta_{rt} + \varepsilon_{it} if lnY_{it-1} \le \sigma \alpha lnY_{it-1} \\ +\beta^u \Delta Temp_{gt} + \gamma \Delta Pre_{gt} + \Omega Z_{it} + \omega X_{it} + \mu_i \\ +q_{it} + w_t + \theta_{rt} + \varepsilon_{it} if lnY_{it-1} > \sigma \end{cases} \quad (2)$$

where the superscripts l and u on the coefficient β indicate, respectively, the lower and upper regime of temperature impacts, conditional on a given threshold σ of lagged consumption level.

4. Data and descriptive statistics

The data used in this work are taken from two different sources.

4.1. Household data

Household data come from the Tanzania National Panel Surveys, part of the World Bank collection of household surveys known as Living Standards Measurement Study – Integrated Survey on Agriculture (LSMS – ISA). In particular, this panel consists of three surveys: 2008 – 2009; 2010–2011; 2012–2013.[9] These three surveys have been cleaned and aggregated using household identification numbers to build a three-round panel. All the monetary values in the surveys have been deflated to convert nominal values in real/constant values, using the Consumer Price Index (CPI) for Tanzania by the World Bank,[10] and they are expressed in Tanzanian shillings at 2013 monetary values. Importantly, we only selected rural households in building the panel, dropping urban households for which confounding factors would have been more likely.[11] After cleaning the data, we are left with a balanced panel of 1585 georeferenced households. This panel includes data on household and, as part of the ISA questionnaire, vegetation time series and geographic variables, as well as data on crops and agriculture.

Finally, data on the monetary value of total crop production and other agricultural characteristics used in Section 5 have been developed by the FAO Rural Income Generating Activities (RIGA) Team starting from the household data contained in the survey questionnaires.

4.2. Weather data

Weather data are taken from NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2), which is a global, gridded data set based on retrospective analysis of historical weather data obtained from satellite images and weather stations (Rienecker et al., 2011). The dataset provides daily temperature measures aggregated into grids that are 1/2° in latitude × 2/3° in longitude (which corresponds roughly to 55 km × 75 km at the equator). The data set are a combination of observed and imputed data points, using observation where and when available, and physics-based interpolation where and when needed. The spatial resolution is the finest available for Tanzania.

We aggregated weather data in two ways. First, we computed long-run averages over the period 1980–2015. These are our

[6] Incidentally, we considered the possibility of a quantile regression model as an alternative and complementary specification, but we ruled out this option because when quantile regression is combined with panel data and a fixed-effect setting, identification and estimation become complicated, since the quantiles of the difference are not equal to the difference in quantiles (Ponomareva, 2010), and interpretation of the coefficient of the treatment variable is altered (Powell, 2016). Estimation gets even worse in case of dynamic models and a small number of time periods, which entail even greater bias (Galvao, 2011; Koenker, 2004). Although some estimators have been proposed to deal with these issues (Galvao, 2011; Powell, 2016), there is not yet an established consensus in literature and empirical applications are rare.

[7] Still, our estimates are robust to the exclusion of the vegetation time series.

[8] In their works on Tanzania, Hirvonen (2016) clusters standard errors at the village level, Bengtsson (2010) at the "cluster"-level, i.e. the main stratification unit and the level at which rainfall is observed. Given the absence of village location data due to confidentiality reasons, EA coordinates were the most appropriate choice for the clustering level.

[9] These data are available at: http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,contentMDK:23635561~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html.

[10] http://data.worldbank.org/indicator/FP.CPI.TOTL?page=1.

[11] Although farmers are randomly selected they do not represent a full national representative sample (and we cannot apply the NPS household survey weights). This does not hamper the external validity of our results which are still valid for the subsample of randomly selected farmers.

Table 1
Descriptive statistics.

	Mean	Var	sd	Obs
Food consumption growth rate	−1.696	992.409	31.503	3168
Total consumption growth rate	−1.441	901.549	30.026	3170
Food consumption	584138.1	1.37e+11	533314.7	4755
Total consumption	773108.5	2.84e+11	369904.3	4755
△Temp	0.083	0.105	0.324	3170
△Pre	0.051	0.023	0.153	3170
Temp	23.755	7.260	2.694	3170
Pre	117.998	589.714	24.284	3170
Long-run average temperature	23.658	6.924	2.631	4755
Long-run average precipitation	114.747	576.907	24.019	4755
Household size	5.659	10.029	3.167	4755
Number of infants (<5 years)	0.918	1.147	1.071	4755
Adult education level	4.593	8.338	2.888	4750
Age of the household head	49.615	241.137	15.529	4755
Gender of the household head	0.239	0.182	0.426	4755
Tropical Livestock Units (TLUs)	0.436	1.328	1.152	3653
Total crop production	843322.4	8.32e+11	912,363	3653

Notes: Food consumption growth rate is the annualised percentage change in household per adult equivalent food consumption between t and t − 1. Total consumption growth rate is the annualised percentage change in household per adult equivalent consumption between t and t − 1. Food consumption is household per adult-equivalent food consumption, expressed in Tanzanian shillings. Total consumption is household per adult-equivalent total consumption, expressed in Tanzanian shillings. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Temp is average monthly growing season temperature in the period between interviews. Pre is average monthly growing season precipitation in the period between interviews. Long-run average temperature is the average monthly growing season temperature over the period 1980–2015, expressed in degree Celsius. Long-run average precipitation represents average monthly growing season precipitation over the period 1980–2015, expressed in mm. Adult education level represents the average years of education among adults, where adult means >15 year old. TLUs are per adult-equivalent. Total crop production is expressed in Tanzanian shillings.

climate variables. Second, we built measures of weather for each household. However, temperature at time t is the average monthly temperature in the period between t and $t-12$, expressed in degree Celsius, where t is the month of the interview (which varies between households). Following Hirvonen (2016), we excluded June, July, August and September to better reflect the weather conditions during the growing season (note that we did the same for the climate variables).[12] Precipitation is measured in millimetres over the growing season. Finally, temperature and precipitation *shocks* (or anomalies) at time t are defined as the difference between their values at t and their long-run averages, divided by the long-run standard deviation.

We used latitude and longitude coordinates to link these gridded weather data to household data. Unfortunately, for confidentiality reasons we did not have access to the exact location of households, but only to the average of household GPS coordinates in each enumeration area (EA), for which a random offset within a 5-km range was applied for rural households. Such an offset range, anyway, is not an issue of concern for us given the resolution of our weather data, as temperature anomalies do not vary much over short distances.

Given the risk of incorrect inference when dealing with historical weather data, see Auffhammer et al. (2013), we also run a sensitivity analysis using a different source of weather data, namely the *CRUCY Version 3.23* by the Climatic Research Unit (CRU) of the University of East Anglia (CRU, 2016), which has a resolution of $1/2^\circ$ in latitude $\times$ $1/2^\circ$ in longitude.

4.3. Descriptive statistics

Table 1 provides descriptive statistics for the main variables employed in the empirical analysis. Annualised average total and food consumption growth rates are both negative: they decreased on average by about 1.4 and 1.7 percentage points each year. However, the standard deviation is large for both variables, indicating heterogeneity in the growth paths experienced by rural households. Both temperature and precipitation anomalies were, on average, positive in the timespan considered, but for them as well it is worth noting the huge standard deviation, suggesting substantial heterogeneity in the weather conditions experienced by households living in different geographical areas.

5. Regression results

Tables 2 and 3 report the results from estimating Eq. (1). First, the hypothesis of convergence among households is confirmed: growth rates are negatively and significantly related to 'initial' consumption levels, i.e., on average and *ceteris paribus*, poorer households grow faster. As for the weather variables, Column 1 shows that temperature and precipitation shocks do not significantly affect both food and total consumption growth. However, these aggregate results could hide substantial heterogeneity. Column 2 provides some insight on this issue by interacting both temperature and precipitation with a dummy for being "poor",[13] i.e. a dummy with value 1 for households whose initial food (Table 2) or total consumption (Table 3) is below the median. Including these interactions qualitatively changes the results: temperature shocks now have a positive and weakly significant impact for the "non-poor" households, but a large, negative and significant (at the 5 percent level) impact on household growth for "poor" households, and this holds for both dependent variables (food and total consumption growth). Interpreting these results with respect to the within-standard deviation of temperature shocks (0.237), one standard deviation increase in temperature anomalies decreases household per-adult equivalent food consumption growth by about 2.76%, and household per-adult equivalent total consumption growth by approximately 2.21%, *ceteris paribus*, for households defined as

[12] See http://www.geog.ox.ac.uk/research/climate/projects/undp-cp/UNDP_reports/TanzaniaTanzania.lowres.report.pdf, where it is stated that "the 'short' rains [take place] in October to December and the long rains in March to May, whilst the southern, western and central parts of the country experience one wet season that continues October through April or May". In this way, given the intrinsic difficulty in exactly identifying rainy seasons months for households scattered across the whole country, we excluded months which are not part of any rainy season in Tanzania.

[13] Defining a household as "poor" is of course a relative concept in a setting like rural Tanzania. We check for heterogeneity of impacts with respect to the poorest amongst the poor.

Table 2
FE regressions – Food consumption.

Dependent variable: food consumption growth rate	(1)	(2)	(3)	(4)
L1.Food	-72.965^{***}	-75.796^{***}	-75.808^{***}	-74.281^{***}
	(1.219)	(1.299)	(1.304)	(1.326)
ΔTemp	-1.895	9.925^{*}	11.093^{**}	-338.600^{***}
	(4.750)	(5.332)	(5.449)	(44.868)
Poor × ΔTemp		-21.588^{***}	-21.460^{***}	
		(4.537)	(4.541)	
Hot × ΔTemp			-2.653	
			(3.718)	
ΔPre	0.839	3.259	2.113	-4.941
	(6.673)	(8.386)	(9.339)	(6.622)
Poor × ΔPre		-8.758	-8.482	
		(9.620)	(9.673)	
Hot × ΔPre			2.127	
			(10.264)	
Hot			4.032	
			(3.689)	
L1.Food × ΔTemp				25.713^{***}
				(3.438)
Obs	3164	3164	3164	3164
Adj. R^2	0.831	0.835	0.835	0.841
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Total temperature effect for poorest households		-11.663^{**}	-10.366^{*}	
		(5.091)	(5.308)	
Total temperature effect for households in hot areas			8.441	
			(5.748)	
Total temperature effect for poorest households in hot areas			-13.019^{**}	
			(5.482)	
Total precipitation effect for poorest households		-5.499	-6.329	
		(7.742)	(8.387)	
Total precipitation effect for households in hot areas			4.240	
			(10.401)	

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Food consumption growth rate is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Poor is a dummy with value 1 for households with below median initial food consumption. Hot is a dummy with value 1 for households living in an area with an above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

"poor". Rainfall impacts are insignificant. In Column 3 we also interact weather shocks with a dummy for living in "hot" areas, which takes value 1 for households living in an area with above mean long-run average monthly growing season temperature. Although the interaction between temperature shocks and the dummy for "poor" households stays unchanged in sign, magnitude and significance, the interaction between temperature shocks and a dummy for households living in hotter areas is not significant. Note that living in a hot area has a positive and significant impact per se only on total consumption growth (Table 3). This is very likely due to the fact the hottest areas in Tanzania (coastal regions and Zanzibar) are also the richest ones. Temperature impacts on growth are always larger on food consumption growth than on total consumption growth, consistently with the fact that most households are subsistence farming households. This will be additionally addressed in Section 7, where the channels of the heterogeneity will be investigated.

Finally, Column 4 in both Tables 2 and 3 explores more in detail the relationship between consumption levels, temperature shocks and their impact on growth, by interacting the lagged consumption term (food consumption in Table 2, total consumption in Table 3) with temperature shocks. The results are consistent with the previous findings: the process of convergence is unaltered, the coefficient for temperature shocks is negative and statistically significant, the interaction between lagged consumption and temperature shocks is positive and statistically significant at the 1 percent level, suggesting that the impacts from temperature shocks tend to decrease as households grow richer. Rainfall impacts are still insignificant. Figs. 1 and 2 show the marginal effect of temperature shocks at different lagged consumption levels: the size and sign of the effects of temperature on growth depend level of pre-shock consumption.

Tables 4 and 5 take a closer look, by interacting weather shocks with dummies for initial consumption quartiles. The results, consistent between tables, reveal even further heterogeneity: as can be seen in Column 1 of both tables, households belonging to the poorest initial quartile suffer from a large, negative and statistically significant impact of temperature shocks, while the second and third quartiles do not, and growth for households in the upper initial quartile is positively and significantly affected, revealing heterogeneity in sign rather than size. This core finding is not altered when including the interaction for living in an "hot" area, as shown in Column 2 of both tables. Finally, precipitation shocks are always insignificant.

In sum, depending on initial conditions, the effects of temperature shocks on households' growth is sharply heterogeneous across quartiles, and poorest households are the only ones to be significantly and negatively affected. This is at odds with the implications of the negative and significant coefficient of the lagged consumption term: while there seems to be an ongoing process of convergence, on average and *ceteris paribus*, among households,

Table 3
FE regressions – Total consumption.

Dependent variable: total consumption growth rate	(1)	(2)	(3)	(4)
L1.Cons	−71.193***	−73.532***	−73.618***	−72.671***
	(1.299)	(1.380)	(1.387)	(1.338)
ΔTemp	−0.328	8.494*	9.199*	−319.134***
	(4.198)	(4.478)	(4.736)	(39.811)
Poor × ΔTemp		−17.813***	−17.565***	
		(3.748)	(3.739)	
Hot × ΔTemp			−1.645	
			(3.268)	
ΔPre	0.695	1.777	0.217	−6.080
	(5.848)	(7.452)	(8.279)	(5.597)
Poor × ΔPre		−5.771	−4.890	
		(8.412)	(8.495)	
Hot × ΔPre			2.370	
			(8.380)	
Hot			13.687***	
			(2.855)	
L1.Cons × ΔTemp				23.868***
				(2.988)
Obs	3166	3166	3166	3166
Adj. R^2	0.830	0.833	0.833	0.840
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Total temperature effect for poorest households		−9.319**	−8.366*	
		(4.694)	(4.897)	
Total temperature effect for households in hot areas			7.553	
			(4.846)	
Total temperature effect for poorest households in hot areas			−10.012**	
			(5.117)	
Total precipitation effect for poorest households		−3.994	−4.673	
		(6.747)	(7.235)	
Total precipitation effect for households in hot areas			2.587	
			(8.879)	

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Total consumption growth rate is the annualised percentage change in (ln) household per a.e. total consumption between t and t − 1. L1.Cons is lagged household per a.e. (ln) food consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Poor is a dummy with value 1 for households with below median initial consumption. Hot is a dummy with value 1 for households living in an area with an above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

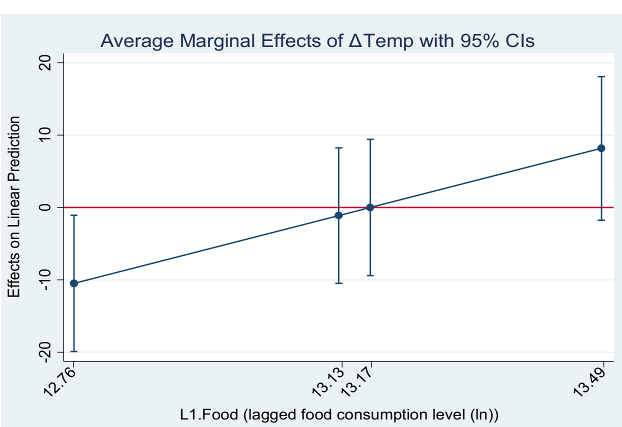

Fig. 1. Marginal effect of ΔTemp on food consumption growth at different lagged food consumption levels.

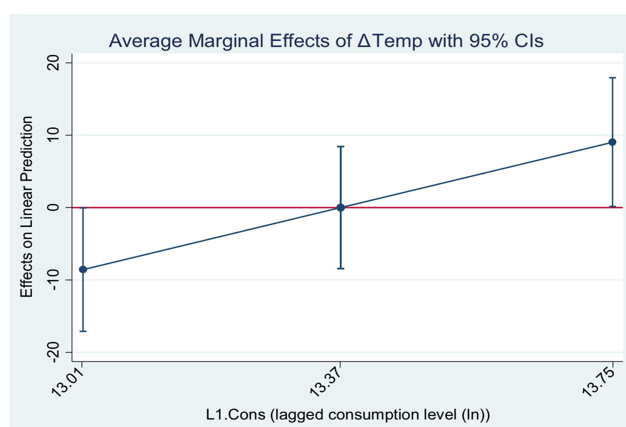

Fig. 2. Marginal effect of ΔTemp on total consumption growth at different lagged total consumption levels.

temperature shocks go in the opposite direction, slowing growth of the poorest households while bolstering growth for the richest ones.

However, we have not precisely identified thresholds of consumption that entail regime changes for temperature shocks. We just interacted shocks with dummies that capture heterogeneity, but these choices are arbitrary. They are not driven by the data. To overcome this drawback, following Carter et al. (2007), we present the results for a fixed-effect panel threshold model using the Hansen (1999) threshold estimator, as implemented by Wang (2015). Threshold models identify structural breaks in the

Table 4
FE initial quartile regressions – Food consumption.

Dependent variable: Food consumption growth rate	(1)	(2)
L1.Food	−77.172***	−77.224***
	(1.344)	(1.351)
q1 × ΔTemp	−19.847***	−19.157***
	(5.164)	(5.338)
q2 × ΔTemp	−5.693	−4.985
	(5.332)	(5.403)
q3 × ΔTemp	4.604	5.234
	(5.659)	(5.944)
q4 × ΔTemp	16.115***	16.784***
	(5.844)	(5.909)
Hot × ΔTemp		−1.386
		(3.677)
q1 × ΔPre	−6.451	−8.752
	(10.031)	(10.497)
q2 × ΔPre	−4.833	−7.239
	(8.634)	(9.354)
q3 × ΔPre	5.244	2.913
	(9.904)	(10.943)
q4 × ΔPre	−2.776	−5.841
	(10.418)	(11.452)
Hot × ΔPre		7.024
		(10.337)
Hot		3.525
		(3.702)
Obs	3164	3164
Adj. R^2	0.837	0.837
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks. Food consumption growth rate is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. q1, q2, q3, q4 are initial food consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5
FE initial quartile regressions – Total consumption.

Dependent variable: Total consumption growth rate	(1)	(2)
L1.Cons	−75.155***	−75.297***
	(1.378)	(1.387)
q1 × ΔTemp	−14.965***	−15.279***
	(5.068)	(5.098)
q2 × ΔTemp	−3.732	−3.738
	(5.504)	(5.666)
q3 × ΔTemp	1.483	1.034
	(4.734)	(5.323)
q4 × ΔTemp	18.664***	18.436***
	(5.565)	(5.624)
Hot × ΔTemp		0.780
		(3.451)
q1 × ΔPre	−3.016	−5.158
	(9.118)	(9.555)
q2 × ΔPre	−6.526	−7.999
	(8.921)	(9.254)
q3 × ΔPre	3.671	0.846
	(8.803)	(9.925)
q4 × ΔPre	−5.478	−8.184
	(10.307)	(10.928)
Hot × ΔPre		6.415
		(8.563)
Hot		14.725***
		(2.894)
Obs	3166	3166
Adj. R^2	0.837	0.837
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. Total consumption growth rate is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1. Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

relationship between variables. Panel threshold models, in particular, are often used in financial and macroeconomic fields. A drawback of fixed-effect models is that they only reflect heterogeneity in intercepts, but cannot identify varying slopes in the relationships between variables. As described by Wang (2015), Hansen's (1999) panel threshold model is characterized by a simple specification but can be very useful to derive policy implications, by identifying single or multiple thresholds (i.e. tipping points) in non-linear structural relationships. In the method proposed by Hansen (1999) and implemented by Wang (2015), the significance of the thresholds is tested using the bootstrap method. In our context, we are looking for thresholds of pre-shock consumption above or below which there is a structural break in the impact of temperature shocks, as illustrated in Eq. (2). Temperature shocks are the regime-dependent variable. Looking at the previous regressions, it appears there is not just one threshold, but two separate and distinct thresholds. The first is the threshold above which impacts turn negative but statistically insignificant; the second the one above which impacts turn positive and significant. We are therefore looking for two, and not just one, consumption level thresholds.

In Table 6 we present the results for this double threshold model using the Hansen estimator.

In Column 1 the dependent variable is food consumption growth, in Column 2 total consumption growth. As hypothesized, we find two thresholds and three regimes: a first threshold below which impacts of temperature shocks are negative and strongly significant, and above which they turn insignificant; and a second threshold from which impacts turn to being positive and strongly significant. Although the positive impact above the upper threshold is much bigger than the negative impact below the lower threshold, the percentage of observations falling below the lower threshold is much higher (47% and 24%, respectively, for food and total consumption) than the percentage of observations above the upper threshold (around 13% in both cases), revealing it is a smaller group of better-off households that drives the significance of the positive impact for the upper quartile. Furthermore, the significance of this positive impact will prove to be sensitive to specification and not supported by evidence on the transmission channels (see Sections 6 and 7). Both thresholds, for both dependent variables, are statistically significant at the 1 percent level, as reported in the threshold tests. After re-converting logs into monetary values, for food

Table 6
Double threshold model – Hansen Estimator.

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	−75.315***	
	(1.452)	
L1.Cons		−73.730***
		(1.517)
ΔPre	−4.776	−9.288
	(7.800)	(6.721)
ΔTemp_Lower regime	−19.651***	−21.032***
	(5.522)	(5.346)
ΔTemp_Medium regime	4.300	−0.032
	(5.334)	(5.049)
ΔTemp_Upper regime	61.024***	34.983***
	(14.604)	(8.204)
Obs	2390	2390
Adj. R^2	0.775	0.772
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Threshold Confidence intervals and effect tests
Column (1) – Food consumption
1) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.089	13.086	13.093
Th-21	13.089	13.084	13.093
Th-22	13.729	13.709	13.733

2) Threshold effect test (bootstrap = 300,300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	5.12e+05	161.770	141.92	0.000	17.715	22.171	27.298
Double	5.04e+05	159.234	50.43	0.000	20.140	22.664	26.723

3) Percentage of observations in each regime:

Lower regime:	47.16%
Medium regime:	39.90%
Upper regime:	12.94%

Column (2) – Total consumption
1) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.297	13.285	13.300
Th-21	12.983	12.979	12.991
Th-22	14.014	14.005	14.024

2) Threshold effect test (bootstrap = 300,300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	4.72e+05	148.891	113.50	0.000	16.957	19.678	26.294
Double	4.61e+05	145.622	73.09	0.000	18.415	22.431	29.031

3) Percentage of observations in each regime:

Lower regime:	23.56%
Medium regime:	63.47%
Upper regime:	12.97%

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the EA and wave levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

consumption we find a lower threshold of approximately 483,594 Tanzanian shillings or, expressed at 2013 Purchasing Power Parity (PPP) values,[14] 803 dollars; and an upper threshold of approximately 917,126 Tanzanian shillings, i.e. about 1523 dollars; for total consumption, instead, the two thresholds are approximately 2,434,956 Tanzanian shillings, approximately 723 dollars, and 1,219,559 Tanzanian shillings, or about 2026 dollars.

Temperature shocks, in sum, slow convergence, and may even cause divergence. This has strong distributional implications and raises the issue of which channels and transmission mechanisms could be responsible for such a sharp heterogeneity of impacts.

[14] For the PPP conversion factor in 2013: https://data.worldbank.org/indicator/PA.NUS.PPP?locations=TZ.

These questions are addressed in Section 7 but, first, Section 6 conducts a number of tests to assess the robustness of our results to different sensitivity analyses, and make sure our findings are not driven by the chosen identification strategy or by properties of the data used.

6. Robustness checks

We explore the robustness of our results with respect to spatial autocorrelation, different weather data and different estimation strategies.

6.1. Conley (1999) standard errors

It is well known that both economic growth and temperature are spatially autocorrelated. One could thus argue that confidence in our results are inflated because we fail to take this into account. We therefore re-run the quartile regressions from Tables 4 and 5 correcting for Conley (1999) standard errors, which are robust to both spatial autocorrelation and heteroskedasticity. The computation of the Conley standard errors is based on a weighing matrix that places greater weight on observations that are closer to each other, and the weights decay to zero after a pre-specified distance cut-off is met. We use the following cut-off points: 50, 75 and 100 km. These regressions are reported in Table A.2 in the Appendix: in Column 1 the dependent variable is food consumption growth, in Column 2 is total consumption growth. The core results are basically unchanged: our findings are not weakened when correcting for spatial autocorrelation and spatially-robust standard errors.

6.2. Different weather data

Results could be driven by properties of the weather data, the selection of weather stations, the homogenization of the data, and the imputation of missing observations. Auffhammer et al. (2013) highlight the risk of using reanalysis data, since reanalysis is conducted with models that, like economic models, are imperfect and contain systematic biases. Moreover, they recommend to always check that results also hold when using a different data source.

For temperature data, we use the *CRUCY Version 3.23* by the Climatic Research Unit (CRU) of the University of East Anglia (CRU, 2016), a gridded dataset which has a resolution of 1/2° in latitude × 1/2° in longitude. While the MERRA-2 Reanalysis data combine information from ground stations, satellites, and other sources with a physical climate model to create gridded weather data products, CRU data are gridded data, statistically interpolated from ground stations (Dell et al., 2014). Table A.3 in the Appendix provides descriptive statistics for the CRU temperature data. ΔTemp is on average almost 5 times bigger compared to average temperature shocks in Table 1. Despite this, the correlation between the two temperature series is more than 90%.

As for rainfall, we use precipitation data that come from the NPS Dataset as part of the ISA module, and our variable is now average total rainfall in the wettest quarter before the interview. These data were taken from the NOAA datasets on African Rainfall Climatology (ARC) data. ARC data blend rain gauge measurements and InfraRed (IR) satellite information to render a daily, high resolution (0.1° × 0.1°) gridded estimate covering the Africa continent.[15] Since data on the long-run standard deviation are not included, we simply define rainfall shocks as level differences from the long-run average. The results are reported in Table A.4 in the Appendix. The pattern of heterogeneity holds, and the effect size is similar, both for the negative impacts on households belonging to the poorest quartile and for the positive impacts for households belonging to the richest quartile. Precipitation shocks are now often significant, and seem to point to heterogeneity as well, but they are also quite sensitive to specification, and since we detect no significant precipitation impacts on crop yields using the same data source (see Section 7), we conclude their significance here is likely incidental.

In sum, our main findings hold when using a different source of weather data.

6.3. Hausman–Taylor regressions

Following Dercon (2004), we repeat our empirical analysis using the Hausman and Taylor (1981) model, which involves partitioning the time-invariant and time-varying vector of variables in two groups each, of which one group of variables is assumed to be uncorrelated with the fixed effect.

The Hausman-Taylor model, being a random-effect model for panel data allows us to include time-invariant variables in our regressions, thus extending identification beyond the within-household intertemporal variation. In addition to region dummies,[16] we add distance to the nearest major road and long-run averages for our weather variables. Given the strong partitioning assumptions implied by this estimation strategy, we adopt a cautious approach, following Dercon (2004): lagged consumption terms and all household controls (with the exception of self-reported covariate shocks) are treated as time-varying endogenous variables; dummies for consumption quartiles are treated as time-invariant endogenous; all weather and geographic variables, both time-varying and time-invariant, are treated as exogenous.

Results can be found in Table A.5 for food consumption growth (Column 1) and total consumption growth (Column 2).[17] Despite stark differences between estimation strategies, the overall picture is consistent with the results from the fixed-effect specification: the convergence process is confirmed, and temperature shocks only harm poorest households, although here also the second poorest quartile is negatively and significantly affected. Interestingly, while the coefficient for the upper quartile is still positive, its magnitude has decreased, and its significance has disappeared in Column (1) and diminished in Column (2). This will be further addressed in the next robustness check. As above, there is no statistically discernible effect of rainfall shocks, while both long-run temperature and precipitation have a positive impact on both food and total consumption growth.

6.4. Two-step difference GMM

As a third, and last, estimation strategy we employ the two-step difference GMM, first proposed by Arellano and Bond (1991). This estimation method controls for the dynamic panel bias due to the presence of the lagged dependent variable and is especially recommended for dynamic panels which exhibit the following characteristics (Roodman, 2006): "1) "small *T*, large *N*" panels, meaning few time periods and many individuals; 2) a linear functional relationship; 3) one left-hand-side variable that is dynamic, depending on its own past realizations; 4) independent variables that are not strictly exogenous, meaning they are correlated with past and possibly current realizations of the error; 5) fixed individual effects;

[15] Data can be found at: ftp://ftp.cpc.ncep.noaa.gov/fews/newalgo_est_dekad/.

[16] Region dummies were included separately from year dummies because the estimation of Hausman-Taylor regressions requires the presence of time-invariant exogenous variables.

[17] Incidentally, although not reported in Table A.5, distance from the nearest major road always has a large and significant effect on growth, consistently with what found by Dercon (2004) in rural Ethiopia, hinting at public infrastructure as another source of divergence among households.

and 6) heteroskedasticity and autocorrelation within individuals but not across them". Arellano–Bond estimation transforms all regressors by differencing, and uses the generalized method of moments (GMM) as the estimation method. Importantly, it adjusts for the potential bias caused by the inclusion of a lagged dependent variable as a regressor. The Hansen-J tests reported ensure the specification is valid, and the standard errors are corrected using Windmeijer (2005) adjustment procedure. In distinguishing between endogenous and exogenous variables, we followed Dercon (2004) and Jalan and Ravallion (2002): lagged consumption terms and all household controls are treated as endogenous, and weather shocks and vegetation time series as exogenous.

The results for the two-step Arellano-Bond GMM estimation are reported in Table A.6.

They are consistent with the fixed-effect and Hausman-Taylor regressions discussed above: heterogeneity of impacts from temperature shocks is confirmed, with a strong and significant impact only for households belonging to the poorest initial quartile. As in the case of the Hausman-Taylor model, temperature impacts for households in the richest quartiles are still positive, but much smaller and not significant anymore. This means that the significance of the positive impact detected using the fixed-effect model is not robust to different estimation strategies and should be interpreted with extreme caution. Finally, precipitation is insignificant.

6.5. Thresholds for the subsample of farming households

As a last sensitivity check, we implement the threshold fixed-effect model only on the subsample of farming households. Farming households are defined as households whose main source of income was farming in at least two waves (cf. Section 7 and Table A.10). Table A.7 presents the estimates. Although the estimated impacts and the related thresholds are physiologically different, the core qualitative findings are unaltered, and the consumption thresholds are close to those detected for the full sample.

7. Transmission channels and mechanisms

Having demonstrated robustness, we now explore why there is such a sharp heterogeneity of impacts and perhaps even a *change in sign* of impacts on household growth depending on initial consumption. We shed light on this question by investigating three main channels: agricultural productivity, productivity, agricultural yields and asset-smoothing.[18]

7.1. Total factor productivity in agriculture

As reviewed above, labour productivity is affected by weather anomalies.

In rural Tanzania, a large share of workers is involved in outdoor work, primarily in farming. Outdoor work is more exposed to heat waves, and agriculture in Tanzania is still largely traditional and thus still involves a lot of manual labour. These characteristics make workers in rural areas vulnerable to stress from temperature shocks, but there could also be significant differences in farmers' characteristics that entail heterogeneity. Labour productivity may thus help explaining the heterogeneous impacts on consumption growth.

Unfortunately, we have no data to build a reliable measure of labour productivity. To partially make up for this shortcoming, we created a variable which captures total factor productivity in agriculture by dividing the monetary value of household total crop production (taken from the FAO Rural Income Generating Activities (RIGA) Team Database[19]) in the 12 months before the interview by the number of family members engaged in agricultural activities in the 12 months before the interview. In a context like rural Tanzania, where subsistence agriculture is still largely predominant, agricultural TFP represents a proxy of (agricultural) labour productivity. Consequently, our left-hand side variable is the growth rate of agricultural TFP between t and $t-1$.[20] Analogously to Eq. (1), we regress this dependent variable on lagged agricultural TFP, temperature and precipitation shocks as well as controls and fixed effects. Since preliminary endogeneity tests (see Table A.8) rejected the assumption of exogeneity of the lagged dependent variable, the model was estimated using two-step difference GMM.

Results are reported in Table 7. Column 1 shows average impacts. Temperature anomalies have a large and significant impact on the growth rate of total factor productivity in agriculture. One within-standard deviation increase in temperature shocks decreases agricultural TFP growth by approximately 5.61%, on average, *ceteris paribus*. Column 2 disentangles this aggregate impact across initial consumption quartiles: there is a large and significant negative effect on the poorest quartile, while impacts are negative but not significant for the other quartiles. Precipitation shocks are insignificant. This overall picture is consistent with the consumption growth regressions, and confirms agricultural TFP (and, indirectly, labour productivity) as one of the transmission channels responsible for the heterogeneity of impacts, but not for the sign change.

Why is there such a discrepancy of impacts on agricultural TFP growth across quartiles? Tables A.9 reports some descriptive statistics that can help clarifying this issue. It shows the average Agricultural Wealth Index for the four initial consumption quartiles. The Agricultural Wealth Index was again taken from the FAO-RIGA Database, and is a specific aggregated index based on a factor analysis of the agricultural assets and technologies used by rural households in the sample. In this context this is useful because it also proxies for the use of technologies that decrease the need for manual labour. The average index is more than three times higher for the upper quartile compared to the poorest quartile, although oddly very low for the third quartile.

Additionally, Table A.10 reports the percentage of households, across quartiles, for which farming was not the main source of income in at least two waves. According to our hypothesis above, households less dependent on farming activities work less outdoors and suffer from a lower impact on agricultural productivity. Farming was the main source of income for about 81% of households in the poorest quartile. This share falls and, for the richest quartile, two-thirds of households depend on farming as the main source of income. This further enhances the influence of weather variability on the productivity of poorest households compared to that of the wealthier households.

We find an heterogenous impact on the growth rate of agricultural TFP, which partially explains heterogeneity of impacts on consumption growth.

[18] In line with the literature on the transmission channels of the weather-economy relationship, we also investigated the health channel by looking at impacts of temperature anomalies on the growth rate of the ratio between health expenditure and total expenditure. However, results were not meaningful and are not reported here.

[19] The FAO-RIGA Database can be found at: http://www.fao.org/economic/riga/riga-database/en/.

[20] We added a small amount (the equivalent of a US dollar) to agricultural TFP values of all households not to lose observations with zeros when calculating growth rates.

Table 7
Agricultural TFP – Two-step Difference GMM.

Dependent variable:	(1) ΔATFP	(2) ΔATFP
L1.ATFP	−70.206***	−70.657***
	(4.677)	(4.785)
ΔTemp	−23.658**	
	(11.942)	
ΔPre	−14.961	
	(14.656)	
q1 × ΔTemp		−32.790**
		(12.933)
q2 × ΔTemp		−20.770
		(13.975)
q3 × ΔTemp		−18.107
		(18.216)
q4 × ΔTemp		−17.618
		(14.574)
q1 × ΔPre		−30.274
		(27.740)
q2 × ΔPre		1.864
		(20.903)
q3 × ΔPre		−18.424
		(27.794)
q4 × ΔPre		−14.348
		(26.282)
Obs	1130	1130
Vegetation time series	Yes	Yes
Household controls	Yes	Yes
Hansen – J test (p)	0.235	0.247

Notes: All specifications include households FE, wave dummies, year FE and quarter of year dummies. Region × time FE and month of interview dummies are used as additional instruments. All household controls are treated as endogenous with the exception of self-reported covariate shocks. ΔATFP is agricultural total factor productivity growth between t and t − 1. L1.ATFP is lagged (ln) agricultural total factor productivity, instrumented using lagged assets and education levels at t − 1. q1, q2, q3, q4 are initial total consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Weather variables and the vegetation time series variables are treated as exogenous. Robust standard errors are in parentheses and are corrected using Windmeijer's procedure. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

7.2. Crop yields

Following the vast literature on the impacts of temperature on crop productivity (see Section 2), we investigate the agricultural yield channel to explain heterogeneity of impacts on consumption growth. Crop yields are defined as quantity produced (in kilograms) divided per hectare of cultivated land. Thanks to the ISA module in the original dataset, we had access to crop data for the two rainy seasons (long and short) preceding the interview month. In investigating the impacts of weather shocks on crops, we must also take into account the possibility of non-linear effects, given the apparent inverted-U and non-linear relationship between temperature and plant growth (Dell et al., 2014; Hirvonen, 2016; Schlenker & Roberts, 2009). In order to do so, we draw from Ahmed et al. (2011), Hirvonen (2016), and Rowhani et al. (2011) works on Tanzania and adopt a specific temperature measure, the number of growing degree days (GDDs) (Schlenker & Roberts, 2009) in the growing season months of the year preceding the interview date. Following the procedure implemented by Hirvonen (2016), we took daily minimum and maximum temperatures from the MERRA-2 data and approximated the diurnal temperature distribution by interpolation using a sinusoidal curve. Growing degree days were then measured by the time of exposure to two distinct temperature ranges, one between 8 °C and 34 °C and the other above 34 °C, since exposure to temperatures above 34 °C is considered harmful for crop yields[21] (Hirvonen, 2016). Therefore, in our regressions we included two distinct variables:

Table 8
Crop yields.

Dependent variable: Crop yield	(1)	(2)	(3)	(4)
Number of GDDs (8–34 °C)	0.000	0.000	0.000	
	(0.001)	(0.001)	(0.001)	
Number of GDDs (34 + °C)	−0.020**	−0.023**	−0.022**	
	(0.010)	(0.010)	(0.010)	
Precipitation	−0.000	−0.000	−0.000	
	(0.002)	(0.002)	(0.002)	
(Precipitation)^2	0.000	0.000	0.000	
	(0.000)	(0.000)	(0.000)	
Irrigated farms × Number of GDDs (8–34 °C)		−0.000		
		(0.000)		
Irrigated farms × Number of GDDs (8–34 °C)		0.031		
		(0.025)		
Irrigated farms		−0.041		
		(1.184)		
Maize & paddy non-specializers × Number of GDDs (8–34 °C)			−0.000	
			(0.000)	
Maize & paddy non-specializers			0.460	
			(1.099)	
q1 × Number of GDDs (34 + °C)				−0.052***
				(0.016)
q2 × Number of GDDs (34 + °C)				−0.020
				(0.015)
q3 × Number of GDDs (34 + °C)				−0.017
				(0.011)
q4 × Number of GDDs (34 + °C)				0.011
				(0.021)
q1 × Precipitation				0.001
				(0.003)
q2 × Precipitation				−0.000
				(0.004)
q3 × Precipitation				−0.000
				(0.002)
q4 × Precipitation				−0.002
				(0.004)
q1 × (Precipitation)^2				−0.000
				(0.000)
q2 × (Precipitation)^2				−0.000
				(0.000)
q3 × (Precipitation)^2				0.000
				(0.000)
q4 × (Precipitation)^2				0.000
				(0.000)
Obs	3537	3534	3537	3537
Adj. R^2	0.595	0.596	0.599	0.599
Vegetation time series	Yes	Yes	Yes	Yes
Total effect of Number of GDDs (8–34 °C) for irrigated farms		0.000		
		(0.000)		
Total effect of Number of GDDs (34 + °C) for irrigated farms		0.008		
		(0.027)		
Total effect of Number of GDDs (8–34 °C) for households not specialized in maize and paddy production			0.000	
			(0.001)	
Total effect of Number of GDDs (34 + °C) for households not specialized in maize and paddy production			0.005	
			(0.021)	

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Crop yield is average crop yield (kg/ha) during the previous two rainy seasons. 'Irrigated farms' is a dummy with value 1 for household who made use of irrigation in a given wave. 'Maize & paddy non-specializers' is a dummy with value 1 for households in which maize and paddy account for <50% of total crop production in a given wave. q1, q2, q3, q4 are initial total consumption quartiles. Standard errors are in parentheses and are clustered at the EA and wave levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[21] Descriptive statistics on GDDs can be found in the Appendix, Table A.11.

the number of GDDs in the 8–34 °C temperature range and the number of GDDs above 34 °C, so that we could capture temperature's apparent non-linear relationship with plant growth (Schlenker & Roberts, 2009). We also included average total precipitation during the two wettest quarters before the interview and its squares, using the alternative ARC rainfall data (cf. Tables A.3 and A4), because they use the actual household plot location.

Table 8 reports the results for this specification. The dependent variable is average crop yield during the previous two rainy seasons. In Column 1 we only look at the aggregate impact. The estimates suggest that it is exposure to extreme temperatures (above 34 °C) which is harmful for crop yields. Column 2 includes an interaction between the temperature variables and a dummy taking value 1 for irrigated farms. The harmful effect of extreme temperatures disappears if households make use of irrigation techniques. For these households, exposure to extreme temperatures has a positive but insignificant effect. In Column 3 we check whether this negative effect mainly comes through maize and paddy, two of the most important crops in the country, as suggested by previous literature on the impacts of temperature on crop yields in Tanzania (Ahmed et al., 2011; Rowhani et al., 2011).

Therefore, we include interactions with a dummy for 'Maize & paddy non-specializers', a dummy with value 1 for households in which maize and paddy account for <50% of total crop production in a given wave.[22] As expected, negative effects on crop yields from extreme temperatures are driven by impacts on maize and paddy, and disappear if households are not specialized in the cultivation of these two crops. In Column 4 we decompose the aggregate impact of GDDs by looking at impacts across initial consumption quartiles. Rainfall impacts are close to zero and insignificant. Impacts of GDDs between 8 and 34 °C is essentially zero for all four quartiles. Exposure to extreme temperatures (above 34 °C) has negative and strongly significant impact on crop yields of households in the poorest quartile, a negative and insignificant impact on crop yields of households in the second and third quartiles, and a positive but insignificant impact on crop yields of households in the upper quartile. These results are consistent with the pattern of heterogeneity of temperature shocks on consumption growth.

Why are there such big differences in the impacts from extreme temperatures on crop yields across quartiles? Table A.13 reveals that richer households produce more crops (Column 1) and have more productive plots (Column 2). The heterogeneity of impacts can thus be explained by the fact that richer households are advantaged by better agricultural assets, technologies and soil quality, which make them less vulnerable to the negative impacts entailed by temperature shocks, which conversely have serious welfare consequences for poorest households.

We have yet to account for the sign change for the upper quartile. The use of irrigation is still very limited (Table A.14) and so the use of inorganic fertilizers (Table A.15), but richer households show better conditions. Tables A.16–A.19 in the Appendix show data taken from the ISA module on the use of 'improved' seeds for maize and paddy. Improved seeds are more drought-resistant and can mitigate the negative impacts of extreme temperatures. Tables A.16 and A.17 show that the use of improved maize seeds sharply differs across consumption quartiles. Tables A.18 and A.19 reveal the same pattern with respect to the use of improved paddy seeds.

7.3. Asset smoothing

We have established that the main channels that account for the heterogeneity of impacts on consumption growth are agricultural yields and agricultural productivity. But we did not explain yet why households are not smoothing consumption by drawing on their assets. Drawing from previous theoretical and empirical literature (Barrett & Carter, 2013; Barrett et al., 2006; Carter & Barrett, 2006; Carter & Lybbert, 2012; Carter et al., 2007), we test the two alternative hypothesis of consumption *vs* asset smoothing by repeating the baseline specification but using, as an alternative dependent variable, asset growth instead of consumption growth. Our measure of assets is Tropical Livestock Units (TLUs), again taken from the FAO-RIGA Dataset. Descriptive statistics for TLUs is reported in Table A.20: the gap in TLUs per adult-equivalent across quartiles is evident.

The dependent variable, therefore, is now annualised percentage change in (ln) per a.e. household TLUs between t and t − 1.[23] Table 9 reports the results. In Column 1 we can see that, while convergence among households is confirmed, temperature shocks have, on average, a negative but not significant impact on asset growth. In

Table 9
Asset smoothing.

Dependent variable: Asset growth	(1)	(2)
L1.Assets	−74.762***	−75.053***
	(1.834)	(1.832)
ΔTemp	−5.823	
	(22.094)	
ΔPre	−27.314	
	(32.146)	
q1 × ΔTemp		−2.823
		(24.355)
q2 × ΔTemp		−3.731
		(25.099)
q3 × ΔTemp		−16.042
		(29.640)
q4 × ΔTemp		−4.402
		(28.642)
q1 × ΔPre		66.468
		(44.547)
q2 × ΔPre		−75.504*
		(42.217)
q3 × ΔPre		−80.426*
		(48.702)
q4 × ΔPre		−29.418
		(59.022)
Obs	2223	2223
Adj. R^2	0.800	0.804
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. Asset growth is the annualised percentage change in (ln) household per a.e. household Tropical Livestock Units (TLUs) between t and t − 1. L1.Assets is lagged household per a.e. (ln) asset level (TLUs). q1, q2, q3, q4 are initial consumption quartiles. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. Δ is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the EA and wave levels. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[22] See Table A.12 for descriptive statistics of this dummy.

[23] To calculate asset growth and use logarithms, since many households have no assets at all and this implied the presence of many zeroes in the data, we followed the method implemented in Carter et al. (2007) and increase all livestock assets per adult-equivalent by the same small increment (namely the minimum value in the sample above zero).

Column 2, where we decompose the impacts by consumption quartiles, impacts are always negative, but we do not find any significance.

These findings imply several considerations. First, it was a good choice to look at consumption growth instead of asset growth, following the reasoning in Carter et al. (2007), who argued that in the context of weather shocks such as droughts, characterized by a gradual onset and a prolonged effect (differently from the immediate disruption entailed by environmental shocks such as hurricanes or typhoons), impacts on welfare growth could appear through consumption and not through assets. Indeed, had we chosen asset growth as the dependent variable, we would have found no impacts at all. Second, poorest households in our sample could be performing asset-smoothing, i.e. they might be voluntarily destabilizing their consumption and hold on to their livestock, in order not to sell them and then fall in a poverty trap from which there could be no recovery. This is consistent with what Carter et al. (2007) find for Ethiopia, where they note that ''poor households seek to defend their assets in the face of successive droughts rather than liquidate them and perhaps limit their subsequent chances of recovery.''. Alternatively, selling livestock may entail a social stigma. In any case, we are prone to assert that, for the poorest households in our sample, asset smoothing is probably taking place, while the choice of using assets as buffer stocks, one of the main risk-coping strategy hypothesized in literature, was either not adopted or not effective during the survey period (Kazianga & Udry, 2006; Morduch, 1995).

8. Discussion and conclusion

Using the WB LSMS-ISA Tanzania Panel Surveys, we find that temperature shocks have a heterogeneous impact which slows the process of income convergence and enhances inequalities. Specifically, household consumption growth is affected only if initial consumption levels lie below a critical threshold. These micro results are consistent with those found on the relationship between growth, temperature shocks and poverty by macro studies (Dell et al., 2012; Letta & Tol, 2016). This finding is explained by the impacts of temperature anomalies on two interrelated transmission channels: agricultural TFP and crop yields. Farmer households above and below the critical threshold differ. The former derive income from more diversified sources, and the latter are more engaged in outdoor farming. Yields and other agricultural characteristics also differ. Such differences among households may be related to *ex-ante* risk-managing behaviours (Dercon, 2004). For example, poorer risk-averse households may shy away from investing in profitable but risky technologies and stick to low-risk, low-return activities (Dercon, 1996). Poor households may lack access to modern technologies because of credit and liquidity constraints. We do not find a positive effect of temperature shock for the richest households (those that lie above the second threshold). In principle, households in the upper quartile can take advantage of the warmer temperatures through irrigation or via higher prices due to the negative impacts on poorest households. However, there is no robust empirical evidence for this in our analysis.

There are caveats, the first being the limitations of the data. We use a six-year panel with three rounds, so we can only estimate a short-run elasticity between temperature shocks and growth. The weather during the investigated period was close to the long-run mean (cf. Table 1). In other words, the weather shocks were small. This could explain the absence of a significant average impact. Severe droughts may well have much more pervasive consequences, but the poorest households would still suffer most.

Second, convergence is a long-run, multi-decadal process. We observe convergence in the short six year panel, but cannot directly test long-run convergence. Longer and larger household-level panels for developing countries could alleviate these issues, enabling further research to test whether these findings, emerged from short-run elasticities, also hold in the medium or long run. External validity is also an issue: weather variation is *not* climate change. Weather shocks reflect the variance in the current climate, whereas climate change is a change in the mean weather. It is a long-run phenomenon in which other factors, particularly non-linearities and adaptation, could completely alter the nature and magnitude of the current elasticities (Dell et al. 2014).

Third, the detected consumption thresholds are not thresholds in the sense of a poverty trap, below which households are permanently trapped in low income. Temperature shocks slow convergence, but do not reverse it. There are no multiple equilibria, but rather different regimes of impacts separated by pre-shock consumption thresholds.

These *caveats* notwithstanding, a number of key suggestions can be inferred from our analysis about the impacts of climate change. First, development and poverty reduction should be key elements of any climate policy, especially in vulnerable contexts like rural Tanzania. Inequality of impacts will be, within countries other than between countries, the most important challenge posed by climate change. Our empirical results suggest that Tanzania might face a poverty-induced climate trap rather than a climate-induced poverty trap. Policymakers should thus prioritize poverty reduction in the country. This could be achieved in several ways: by modernizing agriculture and closing the yield gap, but also favouring the structural transformation of the economy to make household income less exposed to weather anomalies. Extrapolating from weather to climate, such a qualitative finding is particularly relevant to climate change policy. Sub-Saharan Africa is one of the most vulnerable parts of the world to the threats posed by climate change (Field et al., 2014). Our work supports the Schelling Conjecture (1995; Schelling, 1992) that economic development would reduce vulnerability to climate change. The need for greenhouse gas abatement cannot be separated from the developing world's need for immediate development (Schelling, 1997). More broadly, our results increase the concerns over the distributional implications of climate change impacts, as we show that inequalities of impacts hold at the micro level as they do at the macro level. If the impacts of temperature shocks decrease as households grow richer, fostering growth should be prioritized. The key to Schelling Conjecture in rural Tanzania lies in modernizing agriculture and closing the yield gap, using drought-resistant seeds, reducing outdoor work, diversifying income sources, and enabling and encouraging people to move out of subsistence farming. In other words, in making households less dependent on climate and thus less vulnerable to the negative impacts of weather shocks.

Declaration of interest

None.

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Appendix A

Table A1
Instrumented FE regressions – Endogeneity tests.

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	−98.481*	
	(51.761)	
L1.Cons		−91.758***
		(29.374)
ΔTemp	2.846	2.607
	(7.394)	(4.352)
ΔPre	2.440	−0.306
	(6.178)	(7.209)
Observations	3092	3094
Adjusted R-squared	0.304	0.342
Vegetation time series	Yes	Yes
Household controls	Yes	Yes
Endogeneity tests:		
Regressor	Test	p-value
L1.Food	0.074	0.786
L1.Cons	0.423	0.515

Notes: L1.Food is lagged household per a.e. (ln) food consumption, instrumented using lagged assets and education levels at t − 1. L1.Cons is lagged household per a. e. (ln) total consumption, instrumented using lagged assets and education levels at t − 1. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm Standard errors are in parentheses and are clustered at the household and wave levels .
*p < 0.10, **p < 0.05, ***p < 0.01.

Table A2
FE regressions with spatially-robust SEs.

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	−77.224	
Conley (1999), 50 km cut-off	(0.911)***	
Conley (1999), 75 km cut-off	(0.914)***	
Conley (1999), 100 km cut-off	(0.943)***	
L1.Cons		−75.297
Conley (1999), 50 km cut-off		(1.007)***
Conley (1999), 75 km cut-off		(1.037)***
Conley (1999), 100 km cut-off		(1.087)***
q1 × ΔTemp	−19.157	−15.279
Conley (1999), 50 km cut-off	(3.679)***	(3.246)***
Conley (1999), 75 km cut-off	(3.744)***	(3.255)***
Conley (1999), 100 km cut-off	(3.823)***	(3.252)***
q2 × ΔTemp	−4.985	−3.738
Conley (1999), 50 km cut-off	(3.473)	(3.572)
Conley (1999), 75 km cut-off	(3.392)	(3.485)
Conley (1999), 100 km cut-off	(3.370)	(3.322)
q3 × ΔTemp	5.324	1.034
Conley (1999), 50 km cut-off	(3.704)	(3.466)
Conley (1999), 75 km cut-off	(3.658)	(3.427)
Conley (1999), 100 km cut-off	(3.632)	(3.390)
q4 × ΔTemp	16.784	18.436
Conley (1999), 50 km cut-off	(3.572)***	(3.539)***
Conley (1999), 75 km cut-off	(3.492)***	(3.501)***
Conley (1999), 100 km cut-off	(3.409)***	(3.454)***
Hot × ΔTemp	−1.386	0.780
Conley (1999), 50 km cut-off	(2.280)	(2.118)
Conley (1999), 75 km cut-off	(2.293)	(2.124)
Conley (1999), 100 km cut-off	(2.306)	(2.080)
q1 × ΔPre	−8.752	−5.158
Conley (1999), 50 km cut-off	(7.473)	(6.665)
Conley (1999), 75 km cut-off	(7.185)	(6.487)
Conley (1999), 100 km cut-off	(7.167)	(6.459)
q2 × ΔPre	−7.239	−7.999
Conley (1999), 50 km cut-off	(6.245)	(5.942)
Conley (1999), 75 km cut-off	(6.116)	(5.752)
Conley (1999), 100 km cut-off	(6.288)	(5.596)
q3 × ΔPre	2.913	0.846
Conley (1999), 50 km cut-off	(6.898)	(6.512)
Conley (1999), 75 km cut-off	(6.956)	(6.436)
Conley (1999), 100 km cut-off	(7.128)	(6.434)
q4 × ΔPre	−5.841	−8.184
Conley (1999), 50 km cut-off	(7.080)	(7.142)
Conley (1999), 75 km cut-off	(7.085)	(6.999)
Conley (1999), 100 km cut-off	(7.023)	(6.908)
Hot × ΔPre	7.024	6.415
Conley (1999), 50 km cut-off	(6.520)	(5.557)
Conley (1999), 75 km cut-off	(6.527)	(5.616)
Conley (1999), 100 km cut-off	(6.686)	(5.758)
Hot	3.525	14.725
Conley (1999), 50 km cut-off	(6.588)	(5.201)***
Conley (1999), 75 km cut-off	(6.586)	(5.207)***
Conley (1999), 100 km cut-off	(6.513)	(5.244)***
Obs	3164	3.166
Adj. R^2	0.768	0.765
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies for self-reported idiosyncratic and covariate shocks: ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial consumption quartiles in Column (2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Conley (1999) standard errors are in parentheses and are robust to both spatial and temporal autocorrelation.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table A3
Descriptive statistics – Alternative weather data.

	Mean	Var	sd	Obs
ΔTemp	0.405	0.131	0.363	3170
ΔPre	−21.565	8585.501	92.658	4755
Long-run average temperature	23.948	4.362	2.089	4755
Long-run average precipitation	502.203	19198.690	138.559	4755

Notes: ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1983–2015) average monthly growing season temperature divided by long-run (1983–2013) standard deviation, and expressed in degree Celsius. ΔPre is the difference between total precipitation during the previous wettest quarter and long-run average (2001–2013) total precipitation during the wettest quarter divided by average decadal (2001–2013) standard deviation, expressed in mm. Long-run average temperature is the average monthly growing season temperature over the period 1983–2015, expressed in degree Celsius. Long-run average precipitation represents long-run average (2001–2013) total precipitation during the wettest quarter. Data source is the *CRUCY Version 3.23* by the University of East Anglia for temperature data, and the Tanzania LSMS-ISA NPS surveys for rainfall data.

Table A4
FE initial quartile regressions – Alternative weather data.

Dependent Variables:	(1) ΔFood	(2) ΔFood	(3) ΔCons	(4) ΔCons
L1.Food	−76.191***	−76.234***		
	(1.343)	(1.347)		
L1.Cons			−74.291***	−74.270***
			(1.392)	(1.396)
q1 × ΔTemp	−14.205***	−14.636***	−10.985**	−11.147**
	(4.602)	(4.736)	(4.622)	(4.786)
q2 × ΔTemp	−5.339	−5.963	−3.778	−3.964
	(5.507)	(5.559)	(5.031)	(5.073)
q3 × ΔTemp	−0.051	−0.649	−1.797	−2.111
	(5.768)	(5.838)	(4.809)	(4.931)
q4 × ΔTemp	15.130**	14.725**	19.063***	18.940***
	(5.897)	(5.906)	(5.058)	(5.155)
Hot × ΔTemp		2.090		2.623
		(2.453)		(2.342)
q1 × ΔPre	−0.009	−0.002	−3.819***	−0.004
	(0.011)	(0.012)	(1.295)	(0.011)
q2 × ΔPre	−0.001	0.007	1.124	0.003
	(0.010)	(0.010)	(0.763)	(0.011)
q3 × ΔPre	0.019**	0.027**	0.407	0.017
	(0.009)	(0.011)	(1.169)	(0.011)
q4 × ΔPre	0.025**	0.036***	5.007***	0.030**
	(0.010)	(0.013)	(1.250)	(0.014)
Hot × ΔPre		−0.021*		−0.018
		(0.012)		(0.011)
Hot		2.193		10.960***
		(3.445)		(3.198)
Obs	3164	3164	3166	3166
Adj. R^2	0.835	0.836	0.835	0.836
Vegetation time series	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes

Notes: All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial consumption quartiles in Column (2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1983–2015) average monthly growing season temperature, divided by long-run (1983–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between total precipitation during the previous wettest quarter and long-run average (2001 – 2013) total precipitation during the wettest quarter, expressed in mm. Hot is a dummy with value 1 for households living in an area with above mean long-run average monthly growing season temperature. Standard errors are in parentheses and are clustered at the EA and wave levels.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5
Hausman – Taylor regressions.

Dependent variables:	(1) ΔFood	(2) ΔCons
L1.Food	−75.877***	
	(1.302)	
L1.Cons		−74.520***
		(1.277)
q1 × ΔTemp	−21.797***	−18.784***
	(3.888)	(3.625)
q2 × ΔTemp	−9.955***	−9.270**
	(3.818)	(4.064)
q3 × ΔTemp	−1.894	−4.931
	(4.615)	(3.942)
q4 × ΔTemp	6.179	10.206**
	(4.372)	(4.248)
q1 × ΔPre	−10.441	−7.986
	(7.424)	(7.642)
q2 × ΔPre	−3.261	−7.862
	(8.020)	(7.216)
q3 × ΔPre	2.289	−0.584
	(8.345)	(7.064)
q4 × ΔPre	−0.020	−1.665
	(8.364)	(8.918)
Long-run average temperature	1.049*	1.246**
	(0.557)	(0.588)
Long-run average precipitation	0.132**	0.129*
	(0.067)	(0.069)
Obs	3164	3166
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Notes: All specifications include wave, region, year and quarter of year dummies. All household controls are treated as time-varying endogenous variables with the exception of self-reported covariate shocks. Distance (in KMs) to nearest major road is included and treated as time-invariant exogenous. ΔFood is the between-wave percentage change in (ln) household per a.e. food consumption. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Cons is lagged household per a.e. (ln) consumption and is treated as endogenous. q1, q2, q3, q4 are food consumption quartiles in Column (1) and total consumption quartiles in Column (2); they are all treated as time-invariant, endogenous variables. standard deviation, expressed in mm. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. All the weather variables are treated as exogenous. Standard errors are in parentheses and are clustered at the household level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6
Two-step Difference GMM.

Dependent variables:	(1) ΔFood	(2) ΔCons
L1.Food	−70.120***	
	(7.108)	
L1.Cons		−74.439***
		(5.701)
q1 × ΔTemp	−19.993***	−20.437***
	(6.929)	(6.065)
q2 × ΔTemp	−9.166	−7.303
	(5.769)	(5.928)
q3 × ΔTemp	−7.351	−1.323
	(6.051)	(6.254)
q4 × ΔTemp	4.081	10.417
	(8.389)	(7.461)
q1 × ΔPre	0.806	−2.193
	(9.327)	(9.242)
q2 × ΔPre	−3.949	−0.300
	(10.617)	(10.181)
q3 × ΔPre	8.584	12.033
	(12.051)	(10.431)
q4 × ΔPre	2.755	−3.414
	(12.770)	(12.652)
Obs	1581	1.533
Vegetation time series	Yes	Yes

Table A6 (*continued*)

Dependent variables:	(1) ΔFood	(2) ΔCons
Household controls	Yes	Yes
Hansen – J test (p)	0.584	0.510

Notes: All specifications include households FE, wave dummies, year FE and quarter of year dummies. Region × time FE are used as additional instruments. All household controls are treated as endogenous. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption and is treated as endogenous. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Cons is lagged household per a.e. (ln) consumption and is treated as endogenous. q1, q2, q3, q4 are initial food consumption quartiles in Column (1) and initial total consumption quartiles in Column (2). ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Weather variables and the vegetation time series variables are treated as exogenous. Robust standard errors are in parentheses and are corrected using Windmeijer's procedure. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7
Double threshold model – Subsample of farming households.

Dependent variable:	(1) ΔFood	(2) ΔCons
L1.Food	−75.315***	
	(1.452)	
L1.Cons		−73.730***
		(1.517)
ΔPre	−4.776	−9.288
	(7.800)	(6.721)
ΔTemp_Lower regime	−19.651***	−21.032***
	(5.522)	(5.346)
ΔTemp_Medium regime	4.300	−0.032
	(5.334)	(5.049)
ΔTemp_Upper regime	61.024***	34.983***
	(14.604)	(8.204)
Obs	2390	2390
Adj. R^2	0.775	0.772
Vegetation time series	Yes	Yes
Household controls	Yes	Yes

Threshold Confidence intervals and effect tests
Column (1) – Food consumption
4) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.089	13.085	13.091
Th-21	12.918	12.907	12.921
Th-22	14.190	14.149	14.218

5) Threshold effect test (bootstrap = 300,300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	4.00e+05	167.340	116.93	0.000	17.238	19.887	26.005
Double	3.91e+05	163.908	50.00	0.000	17.726	22.009	26.922

6) Percentage of observations in each regime:

Lower regime:	39.12%
Medium regime:	58.62%
Upper regime:	2.26%

Column (2) – Total consumption
4) Threshold estimator (level = 95):

Model	Threshold	Lower	Upper
Th-1	13.042	13.032	13.045
Th-21	13.042	13.030	13.045
Th-22	14.030	14.013	14.185

Table A7 (*continued*)

5) Threshold effect test (bootstrap = 300,300):

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	3.63e +05	151.866	107.60	0.000	17.772	21.131	24.857
Double	3.52e +05	147.351	73.18	0.000	17.523	21.351	27.319

6) Percentage of observations in each regime:

Lower regime:	29.37%
Medium regime:	61.51%
Upper regime:	9.12%

Notes: Farming households are defined as households whose main source of income was farming in at least two waves. All specifications include households FE, wave dummies, region × year FE and quarter of year dummies. Vegetation time series includes data on changes in crop greenness within growing season and onset of greenness increase and decrease. Household controls include household size, squared household size, age of the household head, squared age of the household head, gender of the household head, number of infants, adult education level and dummies capturing self-reported idiosyncratic and covariate shocks. ΔFood is the annualised percentage change in (ln) household per a.e. food consumption between t and t − 1. ΔCons is the annualised percentage change in (ln) household per a.e. consumption between t and t − 1. L1.Food is lagged household per a.e. (ln) food consumption. L1.Cons is lagged household per a.e. (ln) consumption. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the EA and wave levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A8
Agricultural TFP– Endogeneity test.

Dependent variable:	(1) ΔATFP
L1.ATFP	−227.889
	(220.885)
ΔTemp	−58.596
	(92.139)
ΔPre	−15.059
	(71.783)
Observations	2260
Vegetation time series	Yes
Household controls	Yes

Endogeneity test:

Regressor	Test	p-value
L1.ATFP	7.611	0.0058

Notes: ΔATFP is agricultural total factor productivity growth between t and t − 1. L1.ATFP is lagged (ln) agricultural total factor productivity, instrumented using lagged assets and education levels at t − 1. ΔTemp is the difference between average monthly growing season temperature in the period between interviews and long-run (1980–2015) average monthly growing season temperature, divided by long-run (1980–2015) standard deviation, and expressed in degree Celsius. ΔPre is the difference between average monthly growing season precipitation in the period between interviews and long run (1980–2015) average monthly growing season precipitation, divided by long-run (1980–2015) standard deviation, expressed in mm. Standard errors are in parentheses and are clustered at the household and wave levels.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A9
Descriptive statistics – Agricultural Wealth Index.

Variable: Agricultural Wealth Index				
	Mean	Var	sd	Obs
q1	0.066	1.151	1.073	905
q2	0.097	1.054	1.027	981
q3	0.018	0.841	0.917	931
q4	0.228	1.878	1.370	836

Notes: q1, q2, q3, q4 are initial consumption quartiles.
Agricultural Wealth Index is from the FAO Rural Income Generating Activities (RIGA) Team.

Table A10
Descriptive statistics – Main source of income *Notes:* q1, q2, q3, q4 are initial consumption quartiles.

Variable: Main source of income is not farming (in at least two periods) – % of households		
	Yes	No
Whole sample	24.61	75.39
q1	19.40	80.60
q2	20	80
q3	25.25	74.75
q4	33.75	66.25

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A11
Descriptive statistics – Growing degree days.

	Mean	Var	sd	Obs
Number of GDDs (8–34 °C)	3905.047	389495.400	624.096	4755
Number of GDDs (34 + °C)	3.280	46.273	6.802	4755

Table A12
Descriptive statistics – Maize and paddy as a share of total crop production.

Maize and paddy account for 50% or more of total crop production – % of households		
	Yes	No
q1	50.59	49.41
q2	58.44	41.46
q3	51.60	48.40
q4	47.81	52.19

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A13
Descriptive statistics – Average crop yield and quantity produced.

	(1) Mean quantity (kg)	(2) Mean crop yield (kg/ha)	Obs
q1	1268.625	715.602	876
q2	1452.362	1033.638	965
q3	1479.123	1225.526	903
q4	1762.087	1201.825	793

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A14
Descriptive statistics – Irrigation.

Use of irrigation in the previous long rainy season – % of households		
	Yes	No
q1	1.95	98.05
q2	3.30	96.70
q3	3.84	96.16
q4	6.05	93.95

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A15
Descriptive statistics – Inorganic fertilizers.

Use of inorganic fertilizers in the previous long rainy season – % of households		
	Yes	No
q1	17.65	82.35
q2	19.10	80.81
q3	25.25	74.75
q4	23.46	76.54

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A16
Descriptive statistics – Use of improved maize seeds on at least one plot.

Variable: Use of improved maize seeds on at least one plot across waves – % of households		
	Yes	No
q1	34.16	65.84
q2	41.24	58.76
q3	46.48	53.52
q4	53.46	46.54

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A17
Descriptive statistics – Use of improved maize seeds on at least half plots.

Variable: Use of improved maize seeds on at least half of the household plots across all waves – % of households		
	Yes	No
q1	8.77	91.23
q2	10.65	89.35
q3	18.79	81.21
q4	22.08	77.92

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A18
Descriptive statistics – Use of improved paddy seeds on at least one plot.

Variable: Use of improved maize seeds on at least one plot across waves – % of households		
	Yes	No
q1	19.35	80.65
q2	24.76	75.24
q3	27.03	72.97
q4	27.15	72.85

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A19
Descriptive statistics – Use of improved paddy seeds on at least half plots.

Variable: Use of improved paddy seeds on at least half of the household plots across all waves – % of households		
	Yes	No
q1	4.27	95.73
q2	6.27	93.73
q3	6.61	93.39
q4	16.49	83.51

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Table A20
Descriptive statistics –Tropical Livestock Units per adult-equivalent.

Variable: TLU level p.a.				
	Mean	Var	sd	Obs
Whole sample	0.436	1.328	1.152	3653
q1	0.257	0.337	0.580	926
q2	0.424	1.031	1.016	963
q3	0.410	1.152	1.073	937
q4	0.680	2.890	1.700	827

Notes: q1, q2, q3, q4 are initial consumption quartiles.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2018.07.013.

References

Ahmed, S. A., Diffenbaugh, N. S., Hertel, T. W., Lobell, D. B., Ramankutty, N., Rios, A. R., & Rowhani, P. (2011). Climate volatility and poverty vulnerability in Tanzania. *Global Environmental Change, 21*(1), 46–55.

Alderman, H., Hoddinott, J., & Kinsey, B. (2006). Long term consequences of early childhood malnutrition. *Oxford Economic Papers, 58*(3), 450–474.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies, 58*(2), 277–297.

Auffhammer, M., Hsiang, S. M., Schlenker, W., & Sobel, A. (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*, ret016.

Azariadis, C., & Drazen, A. (1990). Threshold externalities in economic development. *The Quarterly Journal of Economics, 105*(2), 501–526.

Bansal, R., & Ochoa, M. (2011). *Temperature, aggregate risk, and expected returns*. National Bureau of Economic Research.

Barreca, A. I. (2012). Climate change, humidity, and mortality in the United States. *Journal of Environmental Economics and Management, 63*(1), 19–34.

Barrett, C. B., & Carter, M. R. (2013). The economics of poverty traps and persistent poverty: Empirical and policy implications. *The Journal of Development Studies, 49*(7), 976–990.

Barrett, C. B., Marenya, P. P., McPeak, J., Minten, B., Murithi, F., Oluoch-Kosura, W., et al. (2006). Welfare dynamics in rural Kenya and Madagascar. *The Journal of Development Studies, 42*(2), 248–277.

Barrett, C. B., & Swallow, B. M. (2006). Fractal poverty traps. *World Development, 34*(1), 1–15.

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *The American Economic Review*, 1072–1085.

Bengtsson, N. (2010). How responsive is body weight to transitory income changes? Evidence from rural Tanzania. *Journal of Development Economics, 92*(1), 53–61.

Burgess, R., Deschenes, O., Donaldson, D., & Greenstone, M. (2011). *Weather and death in India*. Cambridge, United States: Massachusetts Institute of Technology, Department of Economics.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature, 527*, 235–239.

Cachon, G., Gallino, S., & Olivares, M. (2012). Severe weather and automobile assembly productivity. Columbia Business School Research Paper, (12/37).

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics, 29*(2), 238–249.

Carter, M. R., & Barrett, C. B. (2006). The economics of poverty traps and persistent poverty: An asset-based approach. *The Journal of Development Studies, 42*(2), 178–199.

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World Development, 35*(5), 835–856.

Carter, M. R., & Lybbert, T. J. (2012). Consumption versus asset smoothing: Testing the implications of poverty trap theory in Burkina Faso. *Journal of Development Economics, 99*(2), 255–264.

Challinor, A. J., Wheeler, T. R., Craufurd, P. Q., & Slingo, J. M. (2005). Simulation of the impact of high temperature stress on annual crop yields. *Agricultural and Forest Meteorology, 135*(1), 180–189.

Conley, T. G. (1999). GMM estimation with cross sectional dependence. *Journal of Econometrics, 92*(1), 1–45.

CRU (2016). Climatic Research Unit, University of East Anglia. Retrieved 9 July 2017, from: http://www.cru.uea.ac.uk/data.

De Long, J. B. (1988). Productivity growth, convergence, and welfare: Comment. *The American Economic Review, 78*(5), 1138–1154.

Dell, M., Jones, B. F., & Olken, B. A. (2009). *Temperature and income: reconciling new cross-sectional and panel estimates*. National Bureau of Economic Research.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics, 4*(3), 66–95.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature, 52*(3), 740–798.

Dercon, S. (1996). Risk, crop choice, and savings: Evidence from Tanzania. *Economic Development and Cultural Change, 44*(3), 485–513.

Dercon, S. (2004). Growth and shocks: Evidence from rural Ethiopia. *Journal of Development Economics, 74*(2), 309–329.

Dercon, S., & Christiaensen, L. (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics, 96*(2), 159–173.

Dercon, S., Hoddinott, J., & Woldehanna, T. (2005). Shocks and consumption in 15 Ethiopian villages, 1999–2004. *Journal of African economies*.

Dercon, S., & Krishnan, P. (2000). Vulnerability, seasonality and poverty in Ethiopia. *The Journal of Development Studies, 36*(6), 25–53.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics, 3*(4), 152–185.

Elbers, C., Gunning, J. W., & Kinsey, B. (2007). Growth and risk: Methodology and micro evidence. *The World Bank Economic Review, 21*(1), 1–20.

Fafchamps, M., Udry, C., & Czukas, K. (1998). Drought and saving in West Africa: Are livestock a buffer stock? *Journal of Development economics, 55*(2), 273–305.

Field, C. B., Barros, V. R., Mastrandrea, M. D., Mach, K. J., Abdrabo, M.-K., Adger, N., ... others. (2014). Summary for policymakers. In Climate change 2014: Impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (pp. 1–32). Cambridge University Press.

Gallup, J. L., Sachs, J. D., & Mellinger, A. D. (1999). Geography and economic development. *International Regional Science Review, 22*(2), 179–232.

Galvao, A. F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics, 164*(1), 142–157.

Goldberg, M. S., Gasparrini, A., Armstrong, B., & Valois, M.-F. (2011). The short-term influence of temperature on daily mortality in the temperate climate of Montreal, Canada. *Environmental research, 111*(6), 853–860.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics, 32*(1), 1–26.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics, 93*, 345–368.

Hausman, J. A., & Taylor, W. E. (1981). Panel data and unobservable individual effects. *Econometrica: Journal of the Econometric Society, 1377–1398*.

Heal, G., & Park, J. (2015). *Goldilocks economies? temperature stress and the direct impacts of climate change*. National Bureau of Economic Research.

Hirvonen, K. (2016). Temperature Changes, Household Consumption, and Internal Migration: Evidence from Tanzania. *American Journal of Agricultural Economics* aaw042.

Hoddinott, J., & Kinsey, B. (2001). Child growth in the time of drought. *Oxford Bulletin of Economics and Statistics, 63*(4), 409–436.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of sciences, 107*(35), 15367–15372.

Hsiang, S. M., & Jina, A. S. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones*. National Bureau of Economic Research.

Jalan, J., & Ravallion, M. (2002). Geographic poverty traps? A micro model of consumption growth in rural China. *Journal of applied econometrics, 17*(4), 329–346.

Kazianga, H., & Udry, C. (2006). Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. *Journal of Development Economics, 79*(2), 413–446.

Koenker, Roger (2004). Quantile regression for longitudinal data Special Issue on Semiparametric and Nonparametric Mixed Models. *Journal of Multivariate Analysis, 91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006.

Lemoine, D., & Kapnick, S. (2015). A top-down approach to projecting market impacts of climate change. *Nature Climate Change, 6*(5), 514–519.

Letta, M., & Tol, R. (2016). *Weather, climate and total factor productivity* Working Paper Series No.102-2016. Department of Economics, University of Sussex.

Li, S., Wheeler, T., Challinor, A., Lin, E., Ju, H., & Xu, Y. (2010). The observed relationships between wheat and climate in China. *Agricultural and Forest Meteorology, 150*(11), 1412–1419.

Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics, 107*(2), 407–437.

Moore, F. C., & Diaz, D. B. (2015). Temperature impacts on economic growth warrant stringent mitigation policy. *Nature Climate Change, 5*(2), 127–131.

Morduch, J. (1995). Income smoothing and consumption smoothing. *The Journal of Economic Perspectives, 9*(3), 103–114.

Murphy, K. M., Shleifer, A., & Vishny, R. W. (1989). Industrialization and the big push. *Journal of Political Economy, 97*(5), 1003–1026.

Niemelä, R., Hannula, M., Rautio, S., Reijula, K., & Railio, J. (2002). The effect of air temperature on labour productivity in call centres—a case study. *Energy and Buildings, 34*(8), 759–764.

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences of the United States of America, 103*(10), 3510–3517.

Park, J. (2017). *Will We Adapt? Labor productivity and adaptation to climate change*. Cambridge, Massachusetts, USA: Harvard Environmental Economics Program.

Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in Thailand. *The American Economic Review*, 15–33.

Pindyck, R. S. (2012). Uncertain outcomes and climate change policy. *Journal of Environmental Economics and management, 63*(3), 289–303.
Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature, 51*(3), 860–872.
Ponomareva, M. (2010). *Quantile regression for panel data models with fixed effects and small T: Identification and estimation*. University of Western Ontario.
Porter, J. R., & Semenov, M. A. (2005). Crop responses to climatic variation. *Philosophical Transactions of the Royal Society B: Biological Sciences, 360*(1463), 2021–2035.
Powell, David (2016). *Quantile regression with nonadditive fixed effects*. RAND Working Paper.
Quah, D. T. (1996). Twin peaks: Growth and convergence in models of distribution dynamics. *The Economic Journal*, 1045–1055.
Quah, D. T. (1997). Empirics for growth and distribution: Stratification, polarization, and convergence clubs. *Journal of Economic Growth, 2*(1), 27–59.
Reis, R. (2009). The time-series properties of aggregate consumption: implications for the costs of fluctuations. *Journal of the European Economic Association, 7*(4), 722–753.
Rienecker, M. M., Suarez, M. J., Gelaro, R., Todling, R., Bacmeister, J., et al. (2011). MERRA: NASA's modern-era retrospective analysis for research and applications. *Journal of Climate, 24*(14), 3624–3648.
Roodman, D. (2006). *How to do xtabond2: An introduction to difference and system GMM in*. Stata https://papers.ssrn.com/sol3/papers.cfm?abstract_id=982943.
Rosenzweig, M. R., & Wolpin, K. I. (1993). Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: Investments in bullocks in India. *Journal of Political Economy, 101*(2), 223–244.
Rowhani, P., Lobell, D. B., Linderman, M., & Ramankutty, N. (2011). Climate variability and crop production in Tanzania. *Agricultural and Forest Meteorology, 151*(4), 449–460.
Sachs, J. (2008). The end of poverty: Economic possibilities for our time. *European Journal of Dental Education, 12*(s1), 17–21.
Schelling, T. C. (1992). Some economics of global warming. *The American Economic Review, 82*(1), 1–14.
Schelling, T. C. (1995). Intergenerational discounting. *Energy Policy, 23*(4–5), 395–401.
Schelling, T. C. (1997). The cost of combating global warming: Facing the tradeoffs. *Foreign Affairs*, 8–14.
Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters, 5*(1) 014010.
Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of Sciences, 106*(37), 15594–15598.
Stern, N. (2013). The structure of economic modeling of the potential impacts of climate change: Grafting gross underestimation of risk onto already narrow science models. *Journal of Economic Literature, 51*(3), 838–859.
Sudarshan, A., & Tewari, M. (2013). The economic impacts of temperature on industrial productivity: Evidence from indian manufacturing. ICRIER Working Paper No. 278.
Tittonell, P., & Giller, K. E. (2013). When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture. *Field Crops Research, 143*, 76–90.
Tol, R. S. J. (2016) (Working Paper Series No. 100–2016). In *Dangerous interference with the climate system: an economic assessment* (pp. 100–2016). Department of Economics, University of Sussex.
Tol, R. S. J. (2018). Economic impacts of climate change. *Review of Environmental Economics and Policy, 12*(1), 4–25.
Townsend, R. M. (1995). Consumption insurance: An evaluation of risk-bearing systems in low-income economies. *The Journal of Economic Perspectives, 9*(3), 83–102.
Wang, Q. (2015). Fixed-effect panel threshold model using Stata. *Stata Journal, 15*(1), 121–134.
Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The Review of Economics and Statistics, 91*(1), 1–19.
Weitzman, M. L. (2010). What is the "damages function" for global warming—and what difference might it make? *Climate Change Economics, 1*(01), 57–69.
Welch, J. R., Vincent, J. R., Auffhammer, M., Moya, P. F., Dobermann, A., & Dawe, D. (2010). Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences, 107*(33), 14562–14567.
Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126*(1), 25–51.